Sensor Placement for Effective Coverage and Surveillance in Distributed Sensor Networks

Santpal Singh Dhillon
Dept. of Electrical & Computer Engineering
Duke University, Durham, U.S.A
E-mail: ssd5@ee.duke.edu

Krishnendu Chakrabarty
Dept. of Electrical & Computer Engineering
Duke University, Durham, U.S.A
E-mail: krish@ee.duke.edu

Abstract- **We present two algorithms for the efficient placement of sensors in a sensor field. The proposed approach is aimed at optimizing the number of sensors and determining their placement to support distributed sensor networks. The optimization framework is inherently probabilistic due to the uncertainty associated with sensor detections. The proposed algorithms address coverage optimization under the constraints of imprecise detections and terrain properties. These algorithms are targeted at average coverage as well as at maximizing the coverage of the most vulnerable grid points. The issue of preferential coverage of grid points (based on relative measures of security and tactical importance) is also modeled. Experimental results for an example sensor field with obstacles demonstrate the application of our approach.**

Keywords-Ad hoc wireless sensor networks; preferential coverage; obstacles; sensor detection; sensor field coverage; terrain modeling.

I. INTRODUCTION

Sensor placement directly influences resource management and the type of back-end processing and exploitation that must be carried out with sensed data in distributed sensor networks. A key challenge in sensor resource management is to determine a sensor field architecture that optimizes cost, and provides high sensor coverage, resilience to sensor failures, and appropriate computation/communication trade-offs. Intelligent sensor placement facilitates the unified design and operation of sensor/exploitation systems, and decreases the need for excessive network communication for surveillance, target location and tracking. Sensor placement therefore forms the essential “glue” between front-end sensing and back-end exploitation.

In this work, we present a resource-bounded optimization framework for sensor resource management under the constraints of sufficient grid coverage of the sensor field. The proposed approach offers a unique “minimalistic” view of distributed sensor networks in which a minimum number of sensors are deployed, and they transmit/report a minimum amount of sensed data. Intelligent sensor placement ensures that the ensemble of this data contains sufficient information for the data processing center to subsequently query a small number of sensors for detailed information, e.g. imagery and time series data. The proposed approach is aimed at optimizing the number of sensors and their placement for network provisioning and to support such minimalistic sensor networks.

Sensor deployment must take into account the nature of the terrain, for example obstacles such as buildings and trees in the line of vision for IR sensors, uneven surfaces and elevations for hilly terrains, redundancy due to the likelihood of sensor failures, and the power needed to transmit information between deployed sensors and between a deployed sensor and the cluster head.

We represent the sensor field as a grid (two- or three-dimensional) of points. A target in the sensor field is therefore a *logical object*, which is represented by a set of sensors that *see* it. An irregular sensor field is modeled as a collection of grids. The optimization framework is however inherently probabilistic due to the uncertainty associated with sensor detections. We propose two algorithms for sensor placement that address coverage optimization under the constraints of imprecise detections and terrain properties. The issue of preferential coverage of grid points (based on relative measures of security and tactical importance) is also modeled. We limit our discussion in this paper to fixed sensors. Experimental results for an example sensor field with obstacles demonstrate the application of our approach.

As sensors are used in greater numbers for field operation, efficient deployment strategies become increasingly important. Related work on terrain model acquisition for motion planning has focused on the movement of a robot in an unexplored “sensor field” [1]. While knowledge of the terrain is vital for surveillance, it does not directly solve the sensor placement problem. Self-deployment for mobile sensors based on the notion of potential fields is presented in [8]. However, self-deployment does not provide a solution for case of static sensors that need to be deployed in a specific configuration for applications such as environmental monitoring. A related problem in wireless sensor networks is spatial localization [9]. Localization is particularly important when sensors are not deployed deterministically e.g., when sensors are thrown from airplanes in a battlefield, and for underwater sensors that might move due to drift. A number of techniques for both fine and coarse-grained localization have been proposed recently [6, 10].

The problem of determining the coverage provided by a given placement of sensors has also been discussed in the literature [7]. Sensor placement on two- and three-dimensional grids has been formulated as a combinatorial optimization problem, and solved using integer linear programming [2, 3]. This approach suffers from two main drawbacks. First,

Report Documentation Page

Form Approved
OMB No. 0704-0188

Public reporting burden for the collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to a penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.

1. REPORT DATE **2003**	2. REPORT TYPE	3. DATES COVERED **-**
4. TITLE AND SUBTITLE **Sensor Placement for Effective Coverage and Surveillance in Distributed Sensor Networks**		5a. CONTRACT NUMBER 5b. GRANT NUMBER 5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)		5d. PROJECT NUMBER 5e. TASK NUMBER 5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Defense Advanced Research projects Agency,3701 North Fairfax Drive,Arlington,VA,22203-1714**		8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)		10. SPONSOR/MONITOR’S ACRONYM(S) 11. SPONSOR/MONITOR’S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES
The original document contains color images.

14. ABSTRACT
see report

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			
unclassified	**unclassified**	**unclassified**		**6**	

computational complexity makes the approach infeasible for large problem instances. Second, the grid coverage approach relies on "perfect" sensor detection, i.e. a sensor is expected to yield a binary yes/no detection outcome in every case. There is inherent uncertainty associated with sensor readings, hence sensor detections must be modeled probabilistically.

There exists a close resemblance between the sensor placement problem and the art gallery problem (AGP) addressed by the art gallery theorem [4]. The AGP problem can be informally stated as that of determining the minimum number of guards required to cover the interior of an art gallery. Our sensor placement problem differs from AGP in two fundamental ways: (a) the sensors can have different ranges, unlike in AGP where guards are assumed to have similar capabilities, and (b) unlike the intruder detection by guards, sensor detection outcomes are probabilistic. Other related work includes the placement of a given number of sensors to reduce communication cost [5], and optimal sensor placement for a given target distribution .

The remainder of the paper is organized as follows. In Section 2, we describe our sensor detection model as well as our approach for modeling the terrain. Section 3 describes two procedures for placing sensors to provide adequate coverage of the sensor field. We also show how the placement algorithms can be augmented to provide differential coverage of grid points (based on relative measures of security and tactical importance). Section 4 presents experimental results for various problem instances. A comparison is presented with random sensor placement and uniform placement of sensors to highlight the effectiveness of the proposed algorithms. Finally, Section 5 concludes the paper and describes directions for future work.

II. SENSOR AND TERRAIN MODEL

Sensor placement requires accurate yet computationally feasible sensor detection models. In this work, we first assume that the sensor field is made up of grid points. The granularity of the grid (distance between consecutive grid points) is determined by the accuracy with which the sensor placement is desired.

We assume that the probability of detection of a target by a sensor varies exponentially with the distance between the target and the sensor. This model is illustrated in Figure 1. A target at distance d from a sensor is detected by that sensor with probability $e^{-\alpha d}$. The parameter α can be used to model the quality of the sensor and the rate at which its detection probability diminishes with distance. Clearly, the detection probability is 1 if the target location and the sensor location coincide. For every two grid points i and j in the sensor field, we associate two probability values: (i) p_{ij}, which denotes the probability that a target at grid point j is detected by a sensor at grid point i; (ii) p_{ji}, which denotes the probability that a target at grid point i is detected by a sensor at grid point j. In the absence of obstacles, these values are symmetric, i.e. $p_{ij} = p_{ji}$. However, we will show later in this section that these values need not be equal in the presence of obstacles.

Note that the choice of a sensor detection model does not limit the applicability of the placement algorithm in any way. The detection model is simply an input parameter to the placement algorithm. Alternative detection models can therefore be considered without requiring a major redesign of the placement algorithm.

We next explain how obstacles in the terrain are modeled in this framework. A number of sensors, e.g. IR cameras, require a target to lie in their line of sight. Obstacles cause occlusion and render such sensors ineffective for detection. We assume that some knowledge of the terrain is acquired prior to sensor placement, e.g. through satellite imagery. The obstacles are then modeled by altering the detection probabilities for appropriate pairs of grid points. For example, if an object such as a building or foliage is present in the line of sight from grid point i to grid point j, we set $p_{ij} = 0$. Partial occlusion can also be modeled by setting a non-zero, but small, value for the detection probability.

As an example, consider the two obstacles in the sensor field of Figure 2. The grid points in this figure are numbered from 1 to 16. If we assume that these obstacles are symmetric, then they cause p_{36}, p_{63}, p_{27}, p_{72}, and a number of other detection probabilities to be rendered zero. It is straightforward to determine if for any two grid points i and j, p_{ij} is affected by an obstacle. Each grid point is associated with a pair of (x,y) coordinates in the plane. Similarly, an obstacle also has associated (x,y) coordinates. We determine the equation of the straight line connecting i and j. If the coordinate of the obstacle satisfies this equation, the probability p_{ij} is set to zero.

In many practical instances, obstacles in the sensor field are asymmetric, i.e. $p_{ij}=0$ does not imply that $p_{ji}=0$. This can occur for instance in the case of a hilly terrain. A sensor at lower elevation is unlikely to detect a target at higher elevation, but a sensor at higher elevation can detect a target at lower elevation. This scenario can be easily modeled in our framework by using appropriate detection probability values.

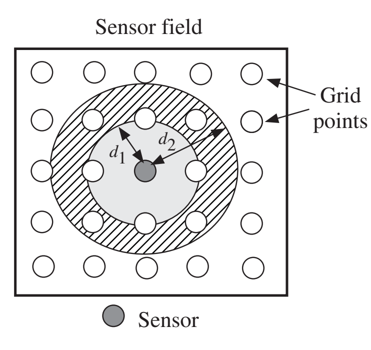

Figure 1. Sensor detection model.

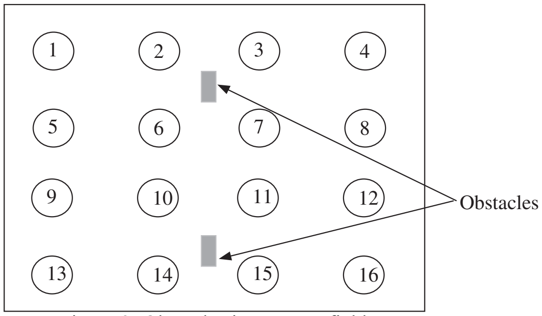

Figure 2: Obstacles in a sensor field.

III. SENSOR PLACEMENT ALGORITHMS

In this section, we describe our algorithms for sensor placement for a given set of detection probabilities in a sensor field (both with and without obstacles). The goal of the sensor placement algorithms is to determine the minimum number of sensors and their locations such that every grid point is covered with a minimum confidence level. We use the term coverage threshold to refer to this confidence level. The coverage threshold T is provided as an input to the placement algorithm. Our objective is to ensure that every grid point is covered with probability of at least T.

The first procedure *MAX_AVG_COV* attempts to maximize the average coverage of the grid points. The second procedure *MAX_MIN_COV* attempts to maximize the coverage of the grid point that is covered least effectively.

We begin by generating a sensor detection matrix $D = [p_{ij}]$ for all pairs of grid points in the sensor field. For an n by n grid, we have a total of n^2 grid points, hence the matrix D consists of n^2 rows and n^2 columns, and a total of n^4 elements.

From the sensor detection matrix D, we determine the miss probability matrix $M = m_{ij}$, where $m_{ij} = 1- p_{ij}$. We do not directly use D in our sensor placement algorithm. Instead, we use the entries in the miss probability matrix M. Both the sensor placement algorithms use a greedy heuristic to determine the best placement of one sensor at a time. The algorithms are iterative, and they place one sensor in the sensor field during each iteration. They terminate either when a preset upper limit on the number of sensors is reached, or sufficient coverage of the grid points is achieved.

We define the vector $M^* = (M_1, M_2,\ldots, M_N)$ to be the set of miss probabilities for the $N = n^2$ grid points in the sensor field. An entry M_i in this vector denotes the probability that grid point i is not collectively covered by the set of sensors placed in the sensor field. At the start of the placement algorithm, the vector M is initialized to the all-1 vector, i.e. $M^* = (1, 1,\ldots, 1)$. Each sensor placed in the sensor field decreases one or more entries in this vector. The placement of a sensor also decreases the order of the miss probability matrix by one as the corresponding row and column in the miss probability matrix become redundant. The pseudocode steps of the first sensor placement algorithm *MAX_AVG_COV* are outlined in Figure 3. Let $M_{\min} = 1-T$ be the maximum value of the miss probability that is permitted for any grid point.

```
Procedure MAX_AVG_COV (M, M*, M_min)
 begin
  num_sensors := 1;
  repeat
   for i := 1 to N do
     Σ_i = m_i1 + m_i2 + ... + m_iN;
    Place sensor on grid point k such that Σ_k is minimum;
   for i := 1 to N do
    M_i = M_i m_ki;  /* Update miss probabilities due to sensor on grid point k */
    Delete k^th row and column from the M matrix
    num_sensors := num_sensors + 1;
  until M_i < M_min for all i, 1 ≤ i ≤ N
      or num_sensors > limit;
 end
```

Figure 3: Pseudocode for the *MAX_AVG_COV* algorithm.

Note that the effectiveness of grid coverage due to an additional sensor is measured in the *MAX_AVG_COV* procedure by the Σ_i parameter. This approach attempts to evaluate the global impact of an additional sensor by summing the changes in the miss probabilities for the individual grid points. We next show how the proposed approach for sensor placement facilitates preferential coverage of grid points. In a typical military force protection or civilian defense scenario, certain installations must be given additional protection. Such installations might include nuclear power plants, command headquarters, or civilian administration centers.

In order to model preferential coverage, we assign a different protection probability pr_i to each grid point i. The miss probability threshold for grid point i is then expressed as $M^i_{\min} = 1-pr_i$. The procedure *MAX_AVG_COV* is modified such that the termination criterion of the repeat/until loop is based on checking that the individual miss probability threshold of each grid point has been reached.

An alternative method for sensor placement is to place a sensor at each iteration at the grid point with minimum coverage. (The first sensor is placed randomly in the grid.) The coverage at every grid point is then calculated and the next sensor is placed at the point of minimum coverage in the grid. This process continues until either all the sensors have been placed or a pre-determined threshold on the coverage is exceeded. The pseudocode steps of the sensor placement algorithm *MAX_MIN_COV* are outlined in Figure 4.

The computational complexity for both *MAX_AVG_COV* and *MAX_MIN_COV* algorithms is $O(kN)$ where k is the number of sensors required for a given coverage threshold. Since k is not known *a priori*, we use N as an upper bound on k and obtain the computational complexity of $O(N^2)$.

The pseudocode descriptions for both *MAX_AVG_COV* and *MAX_MIN_COV* algorithm make the implicit assumption that sensor detections are independent, i.e. if a sensor detects a target at a grid point with probability p_1, and another sensor detects the same target at that grid point with probability p_2, then the miss probability for the target is $(1-p_1)(1-p_2)$.

```
Procedure MAX_MIN_COV (M, M*, M_min)
begin
Place first sensor randomly
num_sensors := 1;
repeat
    for i := 1 to N do
    M_i = M_i m_ki;    /* Update miss probabilities due to sensor on grid point k */
 Place sensor at grid point k such that M_k is max
    Delete k^th row and column from the M matrix
    num_sensors := num_sensors + 1;
until M_i < M_min for all i, 1 ≤ i ≤ N
      or num_sensors > limit;
end
```

Figure 4: Pseudocode for the *MAX_MIN_COV* algorithm.

We have thus far considered the coverage of only the grid points in the sensor field. In order to provide robust coverage of the sensor field, we also need to ensure that the region that lies between the grid points is adequately covered, i.e., every non-grid point has a miss probability less than the threshold M_{min}. Consider the four grid points in Figure 5 that lie on the four corners of a square. Let the distance between these grid points be d^*. The point of intersection of the diagonals of the square is at distance $d^*/\sqrt{2}$ from the four grid points. The following theorem provides a sufficient condition under which the non-grid points are adequately covered by the *MAX_AVG_COV* and *MAX_MIN_COV* algorithms.

Theorem 1: Let the distance between the grid point P_1 and a potential sensor location P_2 be d. Let the distance between adjacent grid points be d^*. If a value of $d + d^*/\sqrt{2}$ is used to calculate the coverage of grid point P_1 due to a sensor at P_2, and the number of available sensors is adequate, the miss probability of all the non-grid points is less than the threshold M_{min} when the algorithms *MAX_AVG_COV* and *MAX_MIN_COV* terminate.

Proof: Consider the four grid points in Figure 5. The center of square, i.e., the point of intersection of diagonals, is at a distance of $d^*/\sqrt{2}$ from each of the four grid points. Every other non-grid point is at a shorter distance (less than $d^*/\sqrt{2}$) from at least one of the four grid points. Thus if a value of $d + d^*/\sqrt{2}$ is used to determine coverage in the *MAX_AVG_COV* and *MAX_MIN_COV* algorithms, we can guarantee that every non-grid point is covered with a probability that exceeds $1 - M_{min}$.

In order to illustrate Theorem 1, we consider an 8 by 8 grid with $\alpha = 0.6$ and $M_{min} = 0.4$. We use Theorem 1 and the *MAX_AVG_COV* algorithm to determine sensor placement and to calculate the miss probabilities for all the centers of the squares. The results shown in Figure 6 indicate that the miss probabilities are always less than the threshold M_{min}, thereby ensuring adequate coverage of the non-grid points.

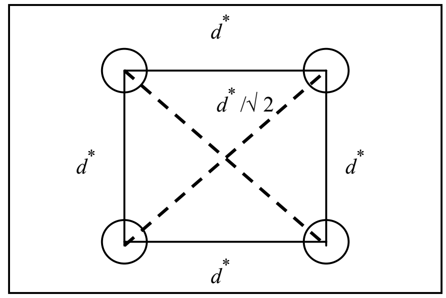

Figure 5: Illustration of the proof of Theorem 1.

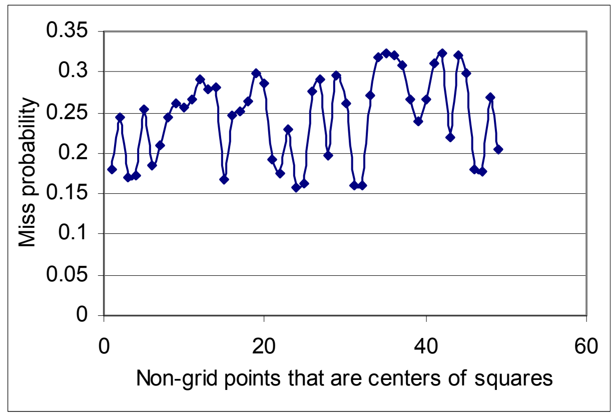

Figure 6: The miss probabilities for the non-grid points that are centers of the squares for an 8 by 8 grid with $\alpha = 0.6$ and $M_{min} = 0.4$.

IV. Experimental Results

In this section, we present experimental results for the two sensor placement algorithms. We first determine sensor placement to minimize the number of sensors for a given coverage threshold. We compare *MAX_AVG_COV* and *MAX_MIN_COV* to a random placement of sensors as well as to uniform placement. We use Theorem 1 throughout to guarantee that all non-grid points are adequately covered. Our first observation is that if there are no obstacles in the sensor field and all sensors are considered identical, random placement is as effective as *MAX_AVG_COV*. This is hardly unexpected since the regularity of these problem instances renders them especially amenable for random placement. We next show that random placement performs significantly worse when the sensor field contains obstacles and when preferential coverage is desired.

Case Study 1

Our first case study was for a 2-dimensional grid with 8 points in each dimension for a total of 64 grid points. We used $\alpha = 0.6$ in calculating the detection probability values for this example. Two obstacles were deterministically placed in the sensor field at specific locations. The results plotted in Figure 7 show that both *MAX_AVG_COV* and *MAX_MIN_COV* algorithms outperform random placement for nearly all values of the miss probability threshold M_{min}. For very small values of the threshold, random placement performs better then *MAX_AVG_COV* but *MAX_MIN_COV* still outperforms random placement.

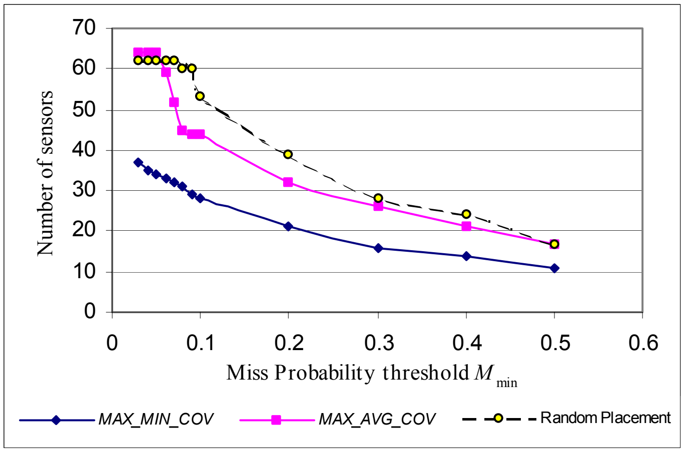

Figure 7: Results for Case Study 1 (8 by 8 grid with two obstacles).

Case Study 2

Our second case study was based on a 2-dimensional grid with 20 grid points in each dimension for a total of 400 grid points. We used $\alpha = 0.5$ in calculating the detection probability values for this example. A number of random obstacles were incorporated into the model, as a result of which a significant number of detection probabilities were either made zero or considerably reduced compared to the values obtained from our detection model. The results shown in Figure 8 indicate that both *MAX_AVG_COV* and *MAX_MIN_COV* outperform random placement of sensors. The number of sensors in *MAX_AVG_COV* is especially small, due in part to the locations of the obstacles in the case study. A number of grid points in this example yield a very small value of Σ_i when a sensors is placed at these grid points using *MAX_AVG_COV* (Figure 3). As a result, the coverage exceeds the threshold $T = 1-M_{min}$ with a small number of sensors. The *MAX_MIN_COV* algorithm is unable to exploit this special property of the problem instance hence it requires more sensors.

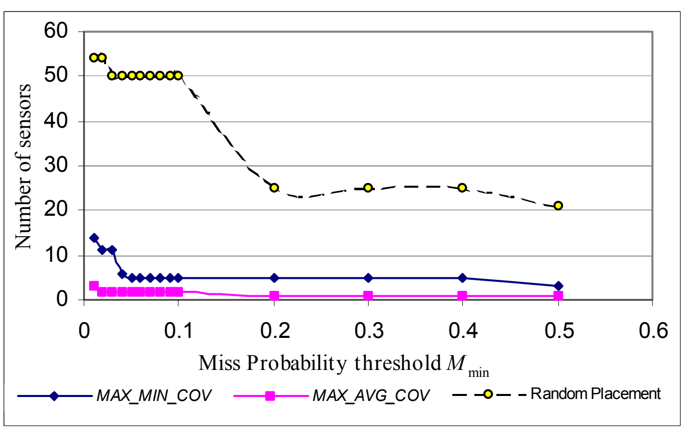

Figure 8: Results for Case Study 2 (20 by 20 grid with randomly placed obstacles).

Case Study 3

In our third case study, we again used a 2-dimensional grid with 8 grid points in each dimension for a total of 64 grid points, and we set α to 0.6. In this case, we placed eight obstacles in the sensor field at specific locations with the detection probability set to zero when any obstacle was on the straight line between the two sensors. We repeat this case study for five different placement of obstacles and averaged the results.

The results are shown in Figure 9. Note that y-axis in this case shows the average number of sensors required for five different cases of obstacle placement. *MAX_AVG_COV* outperforms random placement for smaller values of M_{min}, and is no worse for larger values of M_{min}. However, *MAX_MIN_COV* outperforms both random deployment and *MAX_AVG_COV*.

Case Study 4

In our fourth case study, we considered an 8 by 8 grid with four preset obstacles. We used $\alpha = 0.6$ in calculating the detection probability values. In addition, we considered preferential coverage in this case study. A subset of grid points (marked in Figure 10) was required to be covered with a low miss probability threshold $M_{min} = 0.01$. The threshold for the other grid points in the sensor field was varied to determine the number of sensors needed for random placement and by the procedure. The results in Figure 11 show that *MAX_AVG_COV* outperforms random placement for smaller values of the (variable) miss probability while *MAX_MIN_COV* outperforms both the other deployment strategies for small values of miss probability.

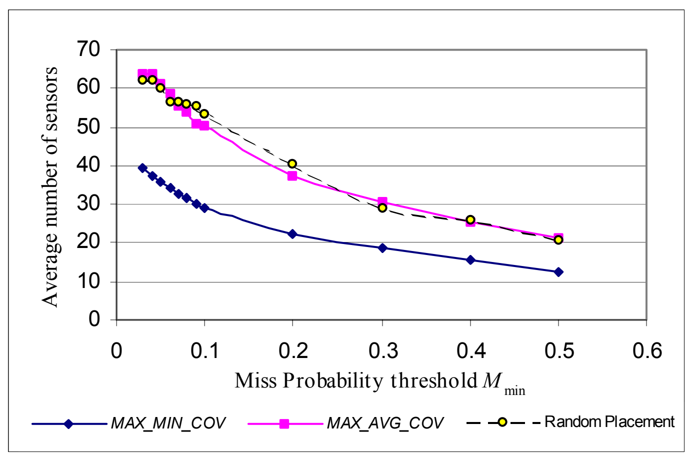

Figure 9: Average results for Case Study 3 (8 by 8 grid with 8 obstacles and 5 different variations of obstacle placement).

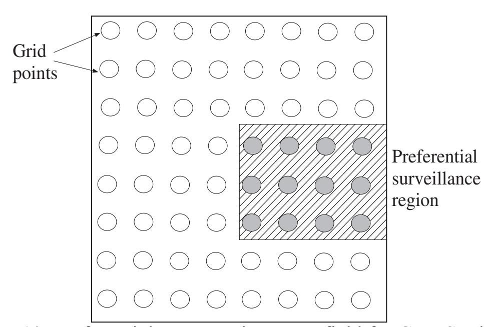

Figure 10: Preferential coverage in sensor field for Case Study 4.

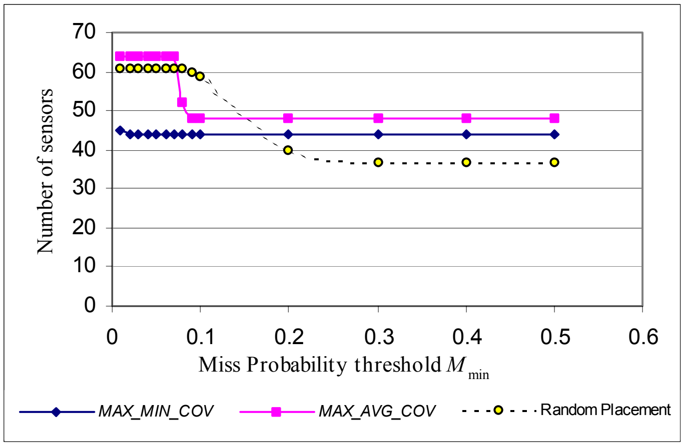

Figure 11: Results for Case Study 4 (8 by 8 grid with four obstacles and preferential coverage).

Case Study 5

We next assumed that we are given a fixed number of sensors that are to be deployed using *MAX_MIN_COV*, *MAX_AVG_COV,* and random placement. We also compared these algorithms to the strategy of uniform (evenly-spaced) deployment of sensors. We considered a 10 by 10 grid with α = 0.5 and no obstacles.

The miss probability for the grid point with the minimum coverage is shown in Figure 12. Uniform placement performs better than random placement for most cases. The *MAX_MIN_COV* algorithm outperforms the other three placement strategies. The results also show that *MAX_AVG_COV* significantly outperforms random placement for smaller values of the miss probability.

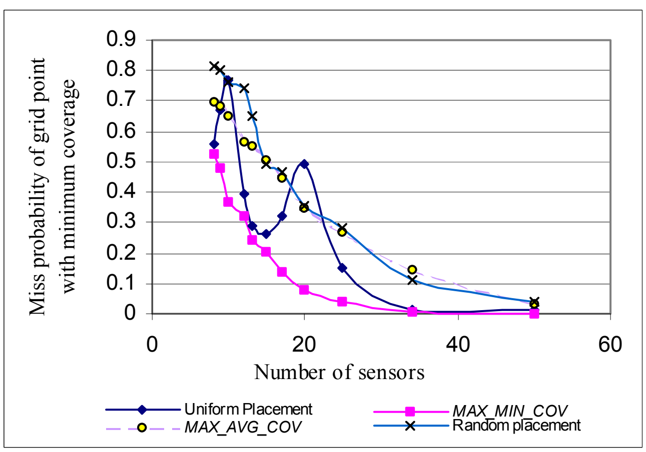

Figure 12: Results for Case Study 5

V. CONCLUSIONS

We have formulated an optimization problem on sensor placement, wherein a minimum number of sensors are deployed to provide sufficient coverage of the sensor field. This approach offers a unique "minimalistic" view of distributed sensor networks in which a minimum number of sensors are deployed and sensors transmit/report a minimum amount of sensed data.

We have presented polynomial-time algorithms to optimize the number of sensors and determine their placement to support such minimalistic sensor networks. The proposed algorithms address coverage optimization under constraints of imprecise detections and terrain properties. The issue of preferential coverage of grid points (based on relative measures of security and tactical importance) has also been modeled. Several case studies for example sensor fields with obstacles and preferential coverage show that the proposed algorithms significantly outperform random and uniform placement of sensors.

We are currently extending this work to the case where the observable domain for a sensor is defined by minimum and maximum ranges and an angular width. Also, we are investigating mobile sensors and obstacles. Finally, we are examining how in addition to determining a sensor location in each iteration, our algorithm can also determine an appropriate sensor from a set of candidate sensors of the same modality. This work is expected to pave the way for an integrated framework for sensor placement that incorporates power management and fault tolerance.

ACKNOWLEDGEMENTS

This research was supported in part by DARPA under grant number N66001-00-1-8946, and in part by Office of Naval Research under grant number N00014-01-1-0712. It was also supported in part by DARPA and Army Research Office under Emergent Surveillance Plexus MURI award no. DAAD19-01-1-0504. Any opinions, findings and conclusions or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the views of DARPA and ARO agencies.

REFERENCES

[1] N. S. V. Rao, S. S. Iyengar, B. J. Oomen and R. L. Kashyap, "On terrain model acquisition by a point robot amidst polyhedral obstacles", *IEEE Journal of Robotics and Automation*, vol. 4, pp. 450-455, August 1988.

[2] K. Chakrabarty, S. S. Iyengar, H. Qi and E. Cho, "Grid coverage for surveillance and target location in distributed sensor networks", *IEEE Transactions on Computers*, vol. 51,pp. 1448-1453, December 2002.

[3] K. Chakrabarty, S. S. Iyengar, H. Qi and E. Cho, "Coding theory framework for target location in distributed sensor networks", *Proc. International Symposium on Information Technology: Coding and Computing*, pp. 130-134, 2001.

[4] J. O'Rourke, *Art Gallery Theorems and Algorithms*, Oxford University Press, New York, NY, 1987

[5] T. Kasetkasem and P. K. Varshney, "Communication Structure Planning for Multisensor Detection Systems", *IEE Proc. Radar, Sonar and Navigation*, vol. 148, pp. 2-8, Feb. 2001.

[6] N. Bulusu, J. Heidemann and D. Estrin, "Adaptive beacon placement", *Proc. Int. Conf. Distributed Computing Systems*, pp. 489-498, 2001.

[7] S. Meguerdichian, F. Koushanfar, M. Potkonjak and M. B. Srivastava, "Coverage problems in wireless ad-hoc sensor networks", *Proc. IEEE Infocom Conference*, pp. 1380-1387, 2001.

[8] A. Howard, M. J. Matarić, and G. S. Sukhatme, "Mobile sensor network deployment using potential fields: A distributed, scalable solution to the area coverage problem", *Proc. International Symposium on Distributed Autonomous Robotics Systems,* pp. 299-308, 2002.

[9] N. Bulusu, J. Heidemann and D. Estrin, "GPS-less low-cost outdoor localization for very small devices", *IEEE Personal Communication Magazine*, vol. 7, pp. 28-34, Oct 2000.

[10] J. Heidemann and N. Bulusu, "Using geospatial information in sensor networks", *Proc. CSTB workshop on Intersection of Geospatial Information and Information Technology,* October 2001.